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A Two Stage Hierarchical Control Approach for the Optimal Energy Management in Commercial Building Microgrids Based on Local Wind Power and PEVs

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***Abstract*— The inclusion of plug-in electrical vehicles (PEVs) in microgrids not only could bring benefits by reducing the on-peak demand, but could also improve the economic efficiency and increase the environmental sustainability. Therefore, in this paper a two stage energy management strategy for the contribution of PEVs in demand response (DR) programs of commercial building microgrids is addressed. The main contribution of this work is the incorporation of the uncertainty of electricity prices in a model predictive control (MPC) based plan for energy management optimization. First, the optimization problem considers the operation of PEVs and wind power in order to optimize the energy management in the commercial building. Second, the total charged power reference which is computed for PEVs in this stage is sent to the PEVs control section so that it could be allocated to each PEV. Therefore, the power balance can be achieved between the power supply and the load in the proposed microgrid building while the operational cost is minimized. The predicted values for load demand, wind power, and electricity price are forecasted by a seasonal autoregressive integrated moving average (SARIMA) model. In addition, the conditional value at risk (CVaR) is used for the uncertainty in the electricity prices. In the end, the results confirm that the PEVs can effectively contribute in the DR programs for the proposed microgrid model.**

***Index Terms*—Demand response (DR), model predictive control (MPC), conditional value at risk (CVaR), plug-in electric vehicles (PEV), wind power, commercial building microgrids.**

I. NOMENCLATURE

	Indices		
i	Index of the PEV	*V2G*	Vehicle to grid
k	Index of time step in the first stage controller	*DR*	Demand response
	Abbreviations	*PEVs*	Plug-in electric vehicles

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SOC	State of the charge	*RERs*	Renewable energy resources
SARIMA	Seasonal autoregressive integrated moving average	*CVaR*	Conditional value at risk
			Variables
$Cost_t(X_t^{ij}, C_t)$	Total operational cost of the commerial bulding microgrid	$\lambda_{PEV,l,u,i}$	Auxiliary variables indicating the SOC constraints violation
D_t	The base load of commercial building microgrid at the t[th] step time	C_t^{GD}	The electricity prices transferred from grid to load at the t[th] step time
X_t^W	Total generated power by wind at the t[th] step time	C_t^{GEV}	The electricity prices transferred from grid to PEV at the t[th] step time
X_t^{ij}	the power transfered from unit i to unit j at the t[th] step time	C_t^{EVG}	The electricity prices transferred from PEV to grid at the t[th] step time
$P_{PEV,i}$	Charging/discharging power of the *i*th PEV	C_t^{WG}	The electricity prices transferred from wind to grid at the t[th] step time
$P_{PEV,agg}^{ref}$	Optimum charge/discharge power reference for aggregated PEVs	η^C	charging efficiency of the PEVs battery
		η^D	discharging efficiency of the PEVs battery
$P_{PEV,agg}$	The charging power of aggregated PEVs. For $P_{PEV,agg} > 0$, PEVs are in charging mode and for $P_{PEV,agg} < 0$, PEVs are in discharging mode.	*w*	weighting factor for the price risk consideration
$E_{PEV,agg}$	Energy stored in the PEVs aggregator		***Parameters***
$E_{PEV,arr}$	Energy stored in the arriving PEVs	*c*	Power to energy conversion factor
$E_{PEV,arr,i}$	Energy stored in the *i*th PEVs when it arrives	P_{km}	Power consumed per kilometer
$E_{PEV,dep}$	Energy stored in the departing PEVs	$C_{Battery}$	Battery capacity of each PEV
$N_{PEV,arr}$	Number of PEV arriving commercial building in each step time	SOC_{min}	Minimum state of the charge of a PEV
d_i	Daily driving distance of the *i*th PEV	SOC_{max}	Maximum state of the charge of a PEV
$N_{PEV,ava}$	Number of plugged-in PEVs	$P_{PEV,max}$	Maximum charging rate of each PEV
SOC_t	State of the charge at the t[th] step time	C_t	the electricity price at the t[th] step time

II. INTRODUCTION

The power system has been facing various technical challenges with the increasing number of distributed generation units mainly based on RERs such as wind and photovoltaic which are utilized especially close to the load centers in order to benefit the grid in reducing the on-peak demand and decreasing the congestion of generation units [1]-[2]. To tackle these problems, a solution could be using microgrids, which are capable of allowing a bidirectional power flow between generation units and load demands. They facilitate the interconnection of distributed power generation units, energy storage systems and different kinds of load in a restricted zone [3]. Microgrids are expected to operate in two modes, i.e., grid connected mode and islanded mode. It is necessary for each microgrid to have a balanced power between generators and consumers [4]. Wind power is one the most attractable sources of RERs which has shown a rapid growth due to its proficiency and accessibility [5]. However, its unpredictable nature makes it an uncertain source of energy which aggravates the conditions of reaching the power balance. Consequently, what is desirable in a microgrid with RERs is to compensate the variation in their power generation. On the other hand, the use of PEVs has recently increased significantly due to its advantages over the internal combustion engine vehicles due to environmental concerns and fossil fuel consumption. Nevertheless, PEVs are regarded as high power consumers since they consume a remarkable amount of power throughout charging procedure which may lead to power shortages, increase on-peak demand, and difficulties related to the reliability of the power grid [6]. Challenges related to using PEVs such as power losses, voltage fluctuations and the power quality deterioration in the current distribution systems are stated in [7]. Thus, the use of PEVs along with the presence of wind power in microgrids in an uncoordinated manner could bring some practical challenges for the demand side management due to their unpredictable nature. This incoordination also increases on-peak demand since the PEV owners tend to connect the PEV to the charging station in the evening when they arrive home or in the morning when they arrive at the work place. Besides, the PEVs remain in stand-by mode up to 96 percent of the time in a day and this time is more than enough for their battery to be fully charged [8]. In addition, in contrast to other electrical appliances, the integration of several PEVs simultaneously connected in parking station could be considered as a potential source for the DR in the power system. This is justified by the amount of the aggregated PEVs charging load by being regarded as a bulk load demand which could be shifted or interrupted during while it is connected to the charging station. So, a coordinated charging schedule for PEVs with power system DR could have a significant improvement on DR through an appropriate management system. In this way, all the PEVs could be entirely charged while the DR is satisfied by shifting or interrupting the charging of PEVs. For this purpose, the aggregated PEVs could be considered as a battery energy storage device in the microgrid and they could be used for reducing the on-peak demand and also for compensating the oscillation of RERs. PEVs could discharge their battery with vehicle-to-grid (V2G) technology when they are parked in the parking station. For this to function, the owners can choose whether they allow their vehicle to participate in this program or not. The benefit is that it allows for the microgrid to discharge their battery when a power imbalance occurs or when the electricity price is high. In this way, a portion of the load dedicated to the charging PEVs could be curtailed so that they can be charged when the electricity price is cheaper or the load is lower instead of charging immediately after connecting to the charging station. As a result, using the PEVs for DR purposes and also coordinating between PEVs and renewable generation in order to improve the power balance in microgrids has been getting an increasing attention from the research community [6]-[8].

Several studies from the literature have been focusing on the contribution of the local power generations (i.e., wind) in different load sectors [9]-[21]. In [9], the coordination between wind power and PEVs is presented by three power dispatching methods in order to create a balance between the power generation and the consumers in the microgrid. In [10] and [11] a control scheme is presented based on integrating PEVs and wind power in order to preserve the grid frequency in a desired range. In [12] a model is employed with the aim of providing DR by considering the cooperative performance between PEVs and wind generators. Four settings are recommended for PEVs and it is concluded that the whole operational cost of the system has been reduced through an optimized charging. In [13] and [14] PEV charging is analyzed under a DR program in the upcoming smart grids in order to reduce the peak demand of the grid. In [13] the PEVs charging pattern and the stochastic nature of the initial SOC is modeled by a normal distribution function. However, the final requested level of SOC is not considered in that study.

In addition, the uncertainty of PEVs in [14] is taken into account based on real-life practice. In [15] different kinds of methods comprising V2G, DR programs, uncontrolled charging and smart charging of PEVs are compared for the day-ahead energy management. In [16] a robust optimization model is presented for a large-scale deployment of PEVs which are considered as a dispatchable energy storage device for DR purposes in order to allow them to supply the load demand and contribute in ancillary services. Overall, with the aim of shifting the bulk demand of PEVs to off-peak times the most of PEVs charging management is based on the different kinds of electricity pricing proposed by the utility, such as setting the price based on real time [17], [18], day-ahead [4], [19], or the consumption time [20]. Nevertheless, in most of these publications, the uncertainties related to electricity price were not taken into account which may lead to inefficient solutions, especially when the price prediction is not very accurate. In addition, the majority of these works only focus on the charging process of PEVs, but less attention is paid to the coordination between PEVs and wind power generation for the purposes of DR.

Due the reasons mentioned above, this paper presents a two stage control approach for DR management based on predictive control. Initially, the PEVs and wind power unit coordination is made for the microgrid in order to create a power balance between power generation and demand. Then, the calculation of the aggregated PEVs power command is sent to the PEVs for analysis. The PEVs controller section optimally allots the computed power for charging or discharging to each individual PEV. To solve this problem an online predictive control problem is proposed with some physical constraints for the microgrid (such as working hours, minimum and maximum charge level for batteries, charging and discharging rate limits and so on). The considered microgrid in this paper is a small to medium size commercial building. Such a microgrid typically uses low voltage distribution system and has approximately up to 1 MW of consumed power under its peak demand [21]. Finally, the key contribution of this work is to utilize PEVs as a potential DR tool in the commercial building microgrid while incorporating the uncertainty of the electricity price in the optimization model by using the CVaR.

The remaining of this paper is organized as follows. The considered case study and its model are presented in Section III. The proposed control approach design is explained in Section IV. Simulation results are presented and discussed in Section V in order to verify the suggested plan. Finally, the paper is concluded in Section VI.

III. System Under Study

The system studied in this paper is a local wind power-based commercial microgrid with several PEVs and load demand (which is the base load without PEV load) and can be observed in Fig. 1. This microgrid is connected to the main grid in order to have the capability of operation in both islanded and grid connected modes.

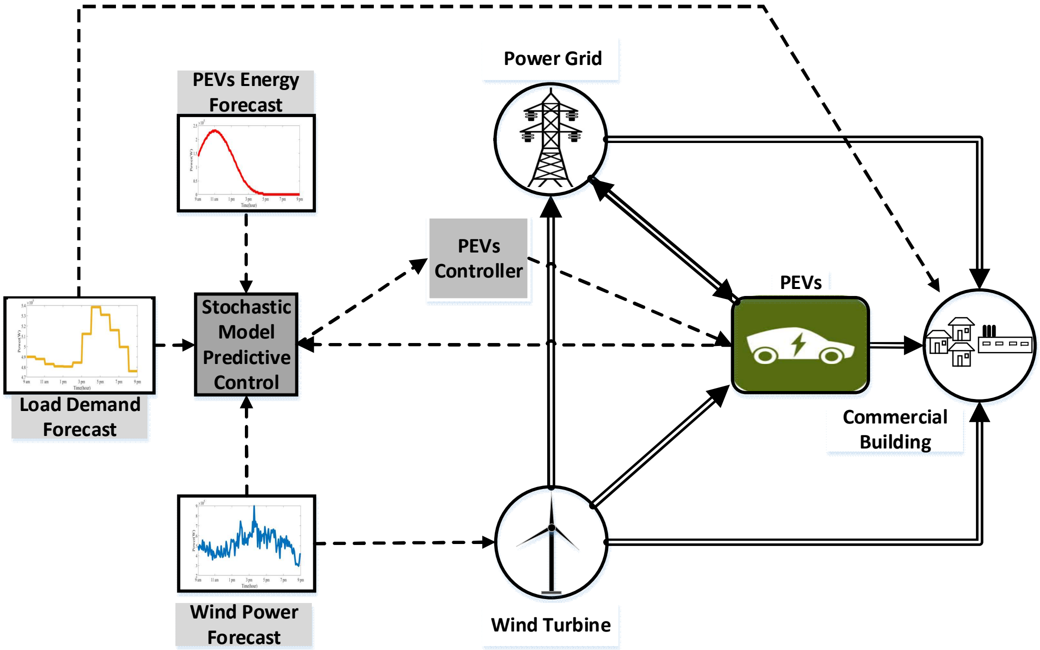

Fig. 1. The schematic of the proposed under study model.

In this study the PEVs are considered as a load or a power supplier, depending if they're charging or discharging, respectively. Only privately owned PEVs are considered for this purpose. It is assumed that only the PEV owners that are the commercial building's employees connect their PEV to the charging station in the morning when they arrive at work. In addition, all of them disconnect their PEV at the 9 PM. For this purpose the arrival time is a stochastic variable but the departure time is deterministic one. The PEVs can be used as an energy storage system to inject power to the microgrid during on-peak demand periods and absorb the excess power of wind power source during off-peak periods. The time horizon for the modelled microgrid is assumed to be between 9:00 AM to 9:00 PM which often contains one period of on-peak and one period of off-peak load. In addition, in order to entice the PEVs owner to participate in this program, an incentives must be dedicated to them. Furthermore, some of the PEV owners (employees) register themselves as dispatchable PEVs and allowing to be demand response candidates. In this way, they commit to be plugged-in during the day in order to be utilized by the commercial building if required. Understandably, despite the dedicated incentives, some PEVs owner disconnect their PEVs from the charging station to depart from the commercial building. When this occurs it is represented as white Gaussian noise in the formulation. In addition, the amount of energy stored in the PEVs which arrive at the commercial building at time step k, is a disturbance to the model and is represented as a stochastic variable $E_{PEV,arr}(k)$. The total number of PEVs is considered to be 100 in this paper. The amount of $E_{PEV,arr}(k)$ depends on the number of PEVs, $N_{PEV,arr}(k)$ and their initial energy ($E_{PEV,arr,i}$) while connecting to the charging station. Furthermore, regarding the stochastic characteristic of the PEVs driving pattern, a statistical model is used for the arrival times and driving distances by considering the statistics of the internal combustion engine vehicles as an approximate reference [22]. By using such data and by using the normal distribution, the maximum likelihood estimation and their curve-fitting, $N_{PEV,arr}(k)$, can be attained. Generally, most of the PEVs arrive before 1 PM and thus $N_{PEV,arr}(k)$ can be modeled by a truncated normal distribution between 9 AM and 1 PM according to equation 1. In addition, from 1 PM to 9 PM, $N_{PEV,arr}(k)$ is assessed to be zero.

$$p\left(N_{PEV,arr}(k)\right) = \frac{1}{\sigma_{N_{PEV,arr,k}}\sqrt{2\pi}} \times \exp\left(-\frac{(N_{PEV,arr}(k)-\mu_{N,k})^2}{2\sigma^2_{N_{PEV,arr,k}}}\right) \tag{1}$$

In which $N_{PEV,arr}$ predicts the number of the PEVs arriving at the commercial building while $N_{PEV,ava}$ is the accumulation of $N_{PEV,arr}$ for each time step and is obtained as follows:

$$N_{PEV,ava}(k+1) = N_{PEV,ava}(k) + N_{PEV,arr}(k) \tag{2}$$

Also, $N_{PEV,arr}$ is an inherently uncertain variable and this makes the $N_{PEV,ava}$ a stochastic variable according to equation (2). In order to simplify the overall system, the uncertainty related to $N_{PEV,ava}$ is considered in the first stage of the proposed approach and so in the second stage it is only taken into account the deterministic one. For this reason, the PEVs arriving at the commercial building at the k^{th} time step, are allowed to be charged or discharged from the next step time that is $(k+1)^{th}$ step time. Thus, the number of PEVs in the k^{th} step time which is required to be managed by the PEV control section is $N_{PEV,ava}(k-1)$ which is a deterministic quantity.

In addition, the daily distance covered by each PEV can be modelled approximately by a logarithmic normal distribution with the mean μ_d=3.20 and variance σ_d=0.88 as presented in (3).

$$p(d_i) = \frac{1}{d\,\sigma_d\sqrt{2\pi}} \times \exp\left(-\frac{(\ln d_i - \mu_d)^2}{2\sigma_d^2}\right) \tag{3}$$

Therefore, the $E_{PEV,arr,i}$ can be obtained as follows:

$$E_{PEV,arr,i} = C_{Battery} - d_i P_{km} \tag{4}$$

Now it is possible to estimate the $E_{PEV,arr,i}(k)$ based on the previous equations. Initially, $\mu_{N_{PEV,arr}}(k)$ is computed, which is the number of PEVs to be added in the time step k. Then the $E_{PEV,arr}(k)$ can be predicted as:

$$E_{PEV,arr}(k) = \sum_{i=1}^{\mu_{N_{PEV,arr,k}}} E_{PEV,arr,i}(k) \tag{5}$$

Finally, by observing Fig. 1, the discrete time model for the proposed commercial microgrid can be expressed by:

$$\begin{aligned} \underbrace{E_{PEV,agg}(k+1)}_{X(k+1)} &= \underbrace{[1]}_{A}\underbrace{E_{PEV,agg}(k)}_{X(k)} + \underbrace{[\eta_c]}_{B}\underbrace{P_{PEV,agg}(k)}_{U(k)} + \underbrace{[1]}_{b'}\underbrace{E_{PEV,arr}(k)}_{Z_E} - \underbrace{[1]}_{c'}\underbrace{E_{PEV,dep}(k)}_{Z_w} \\ \underbrace{P_E(k)}_{Y(k)} &= \underbrace{[1]}_{C}\underbrace{P_{PEV,agg}(k)}_{U(k)} \end{aligned} \tag{6}$$

where, $E_{PEV,agg}$ is modeled as the space state variable, $P_{PEV,agg}$ is regarded as the control input, $E_{PEV,arr}$ is a stochastic disturbance, and $E_{PEV,dep}$ is considered to be white Gaussian noise. Yet, it is assumed that most of the PEVs remain plugged-in throughout the day due to the influence of several incentives designed for this purpose. Hence, the value of $E_{PEV,dep}$ is much smaller than $E_{PEV,arr}$. For this reason, $E_{PEV,dep}$ is not modelled in details. However, in order to consider the unmeasured disturbances in the system, a feedback controller is needed for compensation. So, a simple solution is to create a model predictive control (MPC) controller for this purpose which is later explained in detail. Furthermore, it should be emphasized that other methods of modelling exist regarding the stochastic nature of the initial energy of PEVs [22]-[29]. They are similar to this paper in approach, but their model is more inclusive and they consider other objects such as different kinds of PEVs, the speed, acceleration and the travelling time of PEVs.

IV. The Proposed Control Approach Design

Uncoordinated use of PEVs with wind power in the proposed microgrid exacerbate the power mismatch between power generation and load demand due to the stochastic charactristic of the wind power generation and PEVs. This is unfavorable for both microgrid and main grid and creates difficulties for the demand side management. As a result, with the aim of achieving an optminal operation with the minimum possible cost for the commercial building, the charging procedure of PEVs must be done in a way to enhance the power balance between the generation and load in order to help the demand side control. In addition, it is expected the PEVs to be fully charged before disconnecting from the charging station. Also, it is essential to make sure that PEVs are fully charged at the anticipated plug-out time. In order to achieve these goals, a two stage hierarchical control approach is presented in this paper. In the first stage the power reference for PEVs aggregator is specified by an optimization problem which will be discussed in section IV-C. In the second stage, the aggregated charging power is allocated to each PEVs by its control section. In this way, the first control set is applied to the proposed microgrid. In the next stage, the actual values of the system are measured to repeat the process above. Thus, the feedback controller is used to update the values for the optimization process in the next iteration since it depends on the new measured states. However, for the expansion of the proposed control strategy, a prediction technique is needed for the load, electricity price, and wind power.

A. Prediction of The Wind Power, Load Demand, and Electricity Price

In order to describe the uncertain characteristics of the electricity prices, of the time-varying load demand and wind power, a prediction model is required. The probabilistic planning of each stochastic process can be defined by finding the joint distribution of its random variables which describes both the probabilistic manner of each random variable on its marginal distributions and the interrelations which existed among all of variables (statistical dependencies). In this way, autoregressive moving average (ARMA) models which rely on these two principles is a fitting choice. However, numerous of events periodically (e.g., daily) show a seasonal trend, that means there is a relationship between the observations made during the similar period in successive periods. Besides the seasonal link, there is also a relationship between the observations made during sequential periods. This fact can be seen in the load demand which shows a similar behavior every day and every week, establishing an instance in both daily and weekly seasonality. In these situations a seasonal autoregressive integrated moving average model is needed and is known as SARIMA (an extension of the ARMA model) which considers seasonality and potential seasonal unit

[30]. Suppose y as a stochastic process with a seasonality of order S. The general expression of a seasonal ARIMA model with parameters $(p,d,q)\times(P,D,Q)_S$ can be expressed by:

$$(1-\sum_{j=1}^{p}\phi_j B^j)(1-\sum_{j=1}^{P}\varphi_j B^{jS})(1-B)^d(1-B^S)^D y_t = (1-\sum_{j=1}^{q}\theta_j B^j)(1-\sum_{j=1}^{Q}\vartheta_j B^{jS})\varepsilon_t \tag{7}$$

With a seasonal component of P autoregressive parameters $\varphi_1,\varphi_2,\ldots,\varphi_P$, Q moving average parameters $\vartheta_1,\vartheta_2,\ldots,\vartheta_Q$ and a differentiation order D. In this paper the wind power generation, load demand, and electricity prices are characterized and predicted by a seasonal ARIMA model.

B. Uncertainty Consideration

In this study $f(x,y)$ is the loss related to a set of decision variables x, and is selected from a certain subset X of R^n and the random variable y of R^m. The vector x can be taken as the set of available portfolios, whereas the vector y points out the uncertainty set. The aim is to achieve a value for the decision vector x that can minimize the cost function, conditioned by the uncertainty in vector y. Value at risk (VaR) is one of the most applicable risk measurements and is particularly fitting for loss distribution functions with fat tail behaviors. For a specified confidence level β, the VaR is the smallest loss over the rolling horizon time which is exceeded with probability 1–β according to following equation:

$$VaR_\beta = \min\{\alpha \in R : P\{f(x,y)\le\alpha\}\ge\beta\} for\, 0\le\beta\le 1 \tag{8}$$

Even though VaR is a familiar risk measure used in economic problems, it is a non-coherent risk measure which has negatives points such as non-convexity, non-smoothness, subadditivity etc., which make it an unattractive option in the optimization programming. With the purpose of avoiding this difficulty, there is a desirable alternative risk measure known as conditional value at risk (CVaR) also recognized as average value at risk or mean shortfall. For a given confidence level β, CVaR is defined as:

$$\beta - CVaR = E_y(f(x,y)|f(x,y)\ge\beta - VaR) \tag{9}$$

It specifies the expected conditional value of the cost function, conditioned by this value being larger than β-percentile. In contrast to the traditional robust optimization techniques, the minimization of CVaR is a flexible selection for choosing the objective function. It is capable to improve the optimization performance greatly since it uses distributional data on the uncertain parameter of y. In fact, minimizing the CVaR of the cost leads to the minimization of the risk of the system being exposed to high losses. In addition, for linear cost function problems minimizing CVaR can be expressed as a linear programming problem which is an attractive choice in practical applications. The CVaR can be approximately formulated by:

$$CVaR_\beta = \min(\alpha + \frac{1}{M(1-\beta)}\sum_{i=1}^{M}[f(x,y_i)-\alpha]^+) \tag{10}$$

where, z^{+} indicates the positive elements of z, α is the β-VaR, M is the number of Monte Carlo paths to estimate the expected value of $\beta - CVaR$ in the cost function, and y_i indicates the i^{th} generated path of the uncertain variable. In order to solve this problem, it is generally proposed to substitute the 0^{+} with a set of constraints. Thus, the corresponding equation for minimizing CVaR is formulated as follows:

$$CVaR_{\beta} = \min(\alpha + \frac{1}{M(1-\beta)}\sum_{i=1}^{M} z_i) Subject\ \ to: z_i \geq 0, z_i \geq f(x, y_i) - \alpha \tag{11}$$

C. Problem Formulation of the Proposed Approach

As it is mentioned above, the proposed control approach contains two stages. In the first stage, an optimization problem is solved to in order to minimize the operational cost related to the exchanged power between the main grid and microgrid. It is designed in a way to improve the demand side management by utilizing wind power and PEVs aggregated power in a coordinated manner. In order to yield this purpose, the following cost function has to be minimized:

$$\text{Min} \sum_{T=1}^{N} \text{Cos}t_t(X_t^{ij}, C_t) \tag{12}$$

Considering the prposed system in Fig. 1, wind power is the first priority at each step time to supply the base load. In addition, the aggregated power stored in the PEVs could be used to meet the demand power. Finally, if the wind power and PEVs can not supply the demand, then the main grid is responsible for injecting the shortage power to the commercial building. It assumed that the considered commercial building is open from 9 A.M to 9 PM and this period could be discretized into N intervals of length Δt. Each time step is considered to be 5 minutes in this paper. As a result, 144 points are obtained from 9 A.M to 9 PM for $t = 1, 2, ..., 144$, there are seven decision variable as follows:

$$X_t = (X_t^{GD}, X_t^{GEV}, X_t^{WD}, X_t^{WEV}, X_t^{WG}, X_t^{EVD}, X_t^{EVG}) \tag{13}$$

The superscript *G, W, EV*, and *D* denotes the grid, wind, PEVs and base load demand (without PEVs) of the commercial building, respectively. With this assumption and the fact that the intent is to minimize the operational cost of the commercial building, the total cost of exchanged power in each step time can be obtained as:

$$\text{Cos}t_t(X_t, C_t) = (X_t^{GD}C_t^{GD} + X_t^{GEV}C_t^{GEV}) - (\eta^D X_t^{EVG}C_t^{EVG} + X_t^{WG}C_t^{WG}) \tag{14}$$

For the sake of simplicity, identical values are considered for prices i.e. $C_t^{GD} = C_t^{GEV} = C_t^{EVG} = C_t^{WG} = C_t$, which is acceptable in most energy markets. Thus, the cost function will be equal to:

$$\text{Cos}t_t(X_t, C_t) = C_t.[(X_t^{GD} + X_t^{GEV}) - (\eta^D X_t^{EVG} + X_t^{WG})]. \tag{15}$$

Nevertheless, due to the volatile and unpredictable nature of electricity prices, the strategy above couldn't be an appropriate manner for optimal energy management since abandons the uncertainty of electricity prices. Therefore, it is essential to consider the risk and uncertainty while seeking an optimal approach. For this reason, the final cost function in (16) is obtained by incorporating the cost function represented in (15) into the minimization of the conditional value at risk formulation in (10). In addition, the aggregated charging power of PEVs must be maintained in proper limits. If not, the PEV aggregated batteries will be overcharged when the wind density is high and it won't be fully charged when the wind density is low. If this occurs for a long time, it will remarkably decrease the life time of the battery. Finally, considering risk in electricity prices besides regarding battery limitations and constraints, leads to a linear programming problem as follows:

$$\text{Min} \quad [\sum_{T=1}^{N} (\text{Cos}t_t (X_t, C_t)) + (w \times CVaR_\beta)] \tag{16}$$

Subject to:

$$(X_t^{GD} C_t^{GD} + X_t^{GEV} C_t^{GEV}) - (\eta^D X_t^{EVG} C_t^{EVG} + X_t^{WG} C_t^{WG}) \leq z_i + \alpha \tag{17}$$

$$z_i \geq 0 \tag{18}$$

$$X_t^{WD} = \min\{D_t, X_t^W\} \tag{19}$$

$$X_t^W = X_t^{WEV} + X_t^{WD} + X_t^{WG} \tag{20}$$

$$D_t = X_t^{GD} + \eta^D X_t^{EVD} + X_t^{WD} \tag{21}$$

$$(X_t^{EVD} + X_t^{EVG}) - \eta^C (X_t^{GEV} + X_t^{WEV}) \leq [SOC - SOC_{\min}].N_{PEV,ava}.C_{Battery} \tag{22}$$

$$\eta^C (X_t^{GEV} + X_t^{WEV}) - (X_t^{EVD} + X_t^{EVG}) \leq [SOC_{\max} - SOC].N_{PEV,ava}.C_{Battery} \tag{23}$$

$$\eta^C (X_t^{GEV} + X_t^{WEV}) \leq \Delta S^C.C_{Battery} \tag{24}$$

$$(X_t^{EVD} + X_t^{EVG}) \leq \Delta S^D.C_{Battery} \tag{25}$$

Constraint (19) indicates that the whole power generated by the wind is injected to the load demand when the wind power is lower than commercial building base load. When the power generated by the wind is higher than commercial building demand, the excess power will be injected to the PEVs battery or the main grid. Constraint (21) shows that the power demand of the commercial building is completely supplied by the grid, battery storage or wind power generation. The values of SOC_{min} and SOC_{max} are the minimum and maximum allowable charge level of the PEV battery and constraints (22) and (23) imply that the battery storage level in the next step time remains between two limits. This occurs with the intent of preventing the battery to be damaged during the charging process. In order to ensure that PEVs are fully charged at the expected plug-out time that is 9 P.M and the fact that they require a definite time for fully charging, it is a good decision to change the values of SOC_{min} and SOC_{max} according to the time. For this reason, in this paper, a typical setting for SOC_{min} and SOC_{max} of a lithium-ion battery is considered in the Table I. Moreover, the inequations $0 \le \Delta S^{C} \le 1$ and $0 \le \Delta S^{D} \le 1$ illustrate the maximum amount for charging and discharging rate and constraints (24) and (25) prevent the battery to be charged or discharged faster than the acceptable rates during each step time. After finding the decision variables above by solving the optimization problem, the *SOC* of the aggregated PEVs is obtained according to (6) as:

$$SOC(t) = \frac{E_{PEV,agg}(t)}{N_{PEV,ava} \cdot C_{Battery}} \tag{26}$$

Solving this problem leads to an optimal control action which is the first of them applied to the proposed microgrid. Then, this process is repeated by the actual values of the system such as $E_{PEV,agg}(t+1), E_{PEV,arr}(t+1)$ $and\ P_{PEV,agg}(t+1)$. In addition, the feedback controller is utilized to guarantee that the optimization problem uses the new measured values, and in this way, the impact of the noise $E_{PEV,dep}$ is compensated.

TABLE I. MINIMUM AND MAXIMUM VALUES FOR THE SOC OF PEVS

Time	SOC_{min}	SOC_{max}
From 9:00 AM to 10:40 AM	20%	80%
From 10:40 AM to 12:20 PM	40%	90%
From 12:20 AM to 3:40 PM	50%	95%
From 3:40 AM to 7:00 PM	70%	100%
From 7:00 PM to 9:00 PM	90%	100%

D. PEVs Control Section Design

At the second stage, the PEVs control section is responsible for allocating the charging power from the aggregated PEVs power $P_{PEV,agg}$, which is specified by optimization problem in the first stage, to each individual PEV. As discussed in section II, all of the PEVs arriving in the t^{th} step time, are allowed to be charged or discharged from the next step time i.e., $(t+1)^{th}$ step time. For this reason, the number of PEVs considered for management in the t^{th} step time is equal to $N_{PEV,ava}(t-1)$ which is a deterministic number. So, it is possible to design the PEV control section in a deterministic framework compared to the stochastic from of first stage, because the stochastic nature of arriving PEVs is considered in the first stage. Regarding these matters and the PEV model in (1)-(5), the PEV control section can be expressed as follows:

$$\beta[\sum_{i=1}^{N_{PEV,ava}(t-1)} P_{PEV,i}(t) - P_{PEV,agg}(t)]^2 + (1-\beta) \sum_{i=1}^{N_{PEV,ava}(t-1)} (\lambda_{PEV,l,i}(t)^2 + \lambda_{PEV,u,i}(t)^2) \tag{27}$$

Subject to:

$$\left|P_{PEV,i}(t)\right| \le P_{PEV,\max} \qquad i = 1,2,\ldots,N_{PEV,ava}(t-1) \tag{28}$$

$$0 \le E_{PEV,i}(t) + \eta c P_{PEV,i}(t) \le C_{Battery} \qquad i = 1,2,\ldots,N_{PEV,ava}(t-1) \tag{29}$$

$$E_{PEV,i}(t) + \eta c P_{PEV,i}(t) + \lambda_{PEV,l,i}(t) \ge SOC_{\min}.C_{Battery} \qquad i = 1,2,\ldots,N_{PEV,ava}(t-1) \tag{30}$$

$$E_{PEV,i}(t) + \eta c P_{PEV,i}(t) - \lambda_{PEV,u,i}(t) \le SOC_{\max}.C_{Battery} \qquad i = 1,2,\ldots,N_{PEV,ava}(t-1) \tag{31}$$

$$\lambda_{PEV,l,i}(t), \lambda_{PEV,u,i}(t) \ge 0 \qquad i = 1,2,\ldots,N_{PEV,ava}(t-1) \tag{32}$$

Some of the arriving PEVs may have a SOC lower or higher than the specified limits. In this situations it is impossible to handle their SOC in one cycle in order to come in the desirable range $[SOC_{min}, SOC_{max}]$ because of the maximum charge and discharge rate for PEVs. For this reason, auxiliary variables $\lambda_{PEV,l,i}, \lambda_{PEV,u,i}$ are introduced to soften these limits. In addition, some PEVs connect to the charging station with low charging levels and for short periods of time. In this occasion, they cannot be fully charged before disconnecting from the charger. Thus, it is impossible to make every PEV be completely charged before the plug-out time. In this situation, it is assumed that all of the PEVs are almost fully charged before the use. This is attainable by considering the auxiliary variables in the constraints (30) and (31) which make the PEV control section charge the PEVs battery as much as possible. Solving the problem in (27) with the constraints in (28)-(32) offers the optimum charging command for all of the PEVs connected to the charging station.

V. SIMULATION RESULTS

In order to investigate the accuracy of the proposed control approach in this paper, a simulation is carried out in this section. For this purpose, a system presented in section II (Fig. 1) is used to examine the effectiveness of the suggested strategy. The considered microgrid which consists of 1.5 MW wind power generation, 100 PEVs and base load that has a bidirectional power flow with a main grid. The data of the electricity prices is provided from [30]. The base load demand belongs to a typical commercial microgrid. It is assumed that all of the PEVs are identical. The battery storage parameters of the PEVs is displayed in Table I. In order to have a reasonable approximation for the base load of commercial building, electricity prices and wind power generation, the SARIMA model is used for forecasting in case there is a seasonality effect in their modeling. In Fig. 2, the base load of commercial building and wind power generation are shown over the time horizon of 12 hours between 9 AM and 9 PM. The electricity price is illustrated in Fig. 3. As it is clear from Fig. 2, the wind power is occasionally higher than the base load. This implies that the excess power generated by wind cause a power imbalance in the commercial building. In addition, when there is a power shortage, the same problem occurs. Consequently, in order to improve the demand side management, the first objective is to create a power balance between the generation and the consumption in a way so that the operational cost could be minimized. In addition, the second objective is to satisfy the PEV control section in order to charge PEVs as much as possible so that they could have a satisfactory charging level at the plug-out time. On the other hand, the forecasting electricity prices are generally accompanied with some uncertainty which cause a large effect on the energy management strategy and make it more complex. Disregarding this uncertainty may lead to a non-optimal management. For these reasons, in this paper the CVAR is incorporated in the optimization problem as in equation (16) in order to decrease the risk associated with electricity prices. In Fig. 4, SOC of the aggregated PEVs are depicted for three confidence level $\beta = 0.90$, $\beta = 0.95$ and $\beta = 0.99$. The minimum and maximum value for SOC are also demonstrated in this figure. In addition, Fig.5 indicates the comparison of SOC in two different stats. The first is the SOC of the aggregated PEV using the proposed control approach in this paper with the confidence level $\beta = 0.99$. The second is without the proposed control which is when the PEVs are charged immediately after the connection to the charging station in order to reach the desired charging level. In the second state, there isn't any control of the PEVs. The maximum capacity of the aggregated PEV batteries is also illustrated in this figure. As it is clear from Fig. 4 and Fig. 5, SOC using the proposed approach varies during the simulation time since it assists the demand response management. The optimization problem considers the forecasted energy price in each time step and the associated uncertainty of it, in order to minimize the total operational cost of the commercial building. As the confidence level rises, the operational cost shows a trivial increase. But the system operation will be more robust against price variability. In addition, it is revealed from the Fig. 4 that the aggregated charging power of PEVs for all three confidence levels are kept between 20% and 80% in most of the time in order to increase the life time of the PEV batteries. Furthermore, as the time was getting closer and closer to the plug-out time, the charging level of the aggregated PEVs increases gradually so that the maximum charge level could be reached which means that each PEV is nearly fully charged before disconnecting from the charging station.

When there isn't any control of PEVs, they are charged directly after connecting to the charging station until they are fully charged. This may increase the on-peak demand and increase the system cost. In addition, it may exacerbate the power mismatch in the microgrid. However, by using the proposed approach in this paper it is possible to minimize the power imbalance in the microgrid and help the demand response management. In this way, the operation cost of the system is also significantly reduced. By taking into consideration Figs. 4 and 5, when the wind is lower than the base load, for example between 9 AM and 1 PM, the PEVs are not charged or they are even discharged since they supply the base load in order to minimize the power injection from the main grid into the commercial building in order to decrease its operational cost. On the other hand, when the wind density is high and its power generation is greater than the base load, for instance between 1 P.M. and 5 PM, which is an off-peak load time, and the electricity price is low, the PEVs are charged properly to maximize their charging level. After 5 PM which is on-peak load time and the electricity price goes up, the PEVs are properly discharged in order to supply the load and reduce the operational cost. Finally, during the last instances of the connection to the charging station, when the base load is decreased, the PEVs are charged again so that the desired value of the charging level could be reached before the plug-out time. As a result, the charging and discharging process of the PEVs depend on the base load, wind power, the number of available PEVs and the electricity price. The proposed control approach in this paper tried to create a power balance between production and consumption in a way to minimize the operational cost of the commercial building while considering the uncertainty associated to the electricity price. The power injected into the commercial microgrid is from the main grid and its associated costs are depicted for each time step in Fig. 6 and Fig.7, respectively. Minus power in Fig .6 indicates the reverse direction of the power transfer i.e. from the commercial microgrid to the main grid. When this occurs, the cost sign is also minus which means the commercial building sells the power to the main grid instead of buying it. In addition, as it is clear from Fig. 6, that using the proposed control approach, the power transferred from main grid to the commercial building is varying all the time in order to minimize the total operational cost of the microgrid based on the variability of the wind power, base load, electricity price and PEVs charging level by considering the uncertainty of the electricity price. However, in the uncontrolled approach of PEVs, the power is injected from the grid to the commercial building only when there is shortage in the power supply for the base load and PEVs. The reason is that the uncontrolled PEVs are assumed as a bulk load for commercial building. The total operational cost of the commercial microgrid throughout the simulation is shown in Table III which is 139.5153, 1373.3132 and 128.7805, respectively, and by using the proposed control with $\beta = 0.99$, $\beta = 0.95$ and $\beta = 0.90$, respectively. Moreover, the total operational cost is 206.6003 without the proposed control (when the PEVs are charged immediately after connecting to the charging station until reaching the full charge without any control). As a result, the operational cost of the commercial microgrid has remarkably decreased by using the proposed control at circa 32.47%, 33.54% and 37.67% with $\beta = 0.99$, $\beta = 0.95$ and $\beta = 0.90$, respectively. It becomes evident, as the confidence level goes up, that the system will be more risk averse which translates into higher costs. Finally, it should be mentioned that it's also possible to consider other objective functions for the commercial building rather than minimizing its operational cost. Some examples are: minimizing the power exchange between the main grid and commercial microgrid, generating a pre-specified amount of power by the commercial building or so on. In addition, in order to evaluate the performance of the PEV control section for reference tracking, the simulation result is depicted in Fig. 8. In this figure, the optimized power reference for the aggregated PEVs can be observed, calculated in the first stage, and also the summation of all the individual PEV charging power is illustrated. As it is clear from this figure, the aggregated power reference is tracked by the summation of all the individual PEV charging power.

TABLE II. PARAMETERS FOR PEVS BATTERY ENERGY STORAGE

ΔS^{D}	ΔS^{C}	η^{C}	η^{D}
0.10	0.10	0.95	0.9

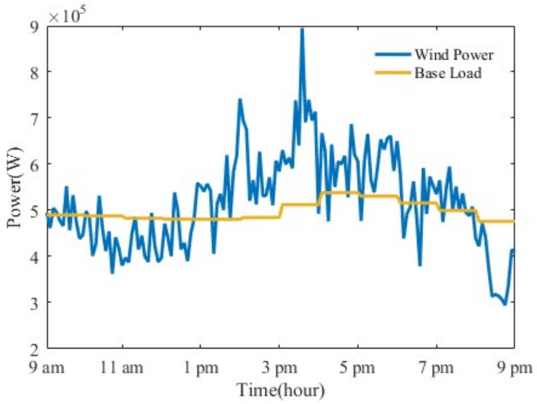

Fig. 2. Base load and wind power.

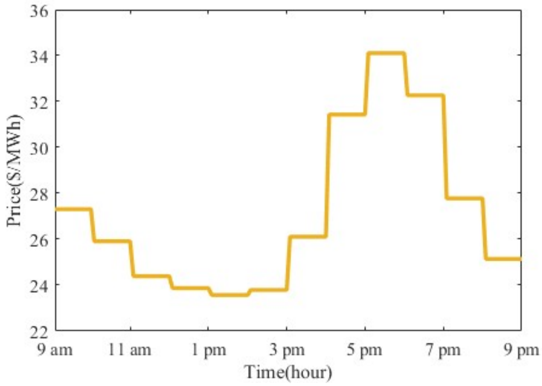

Fig. 3. Electricity Price.

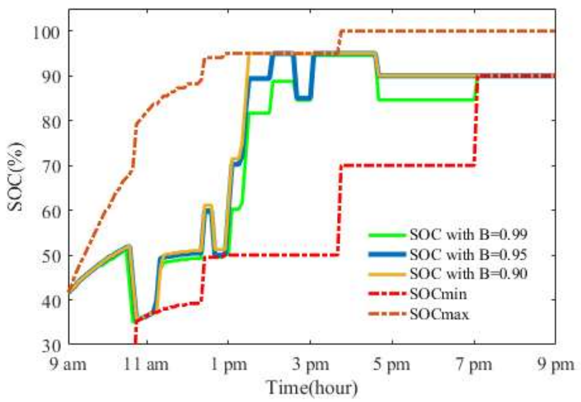

Fig. 4. Aggregated PEVs SOC, SOCmax and SOCmin.

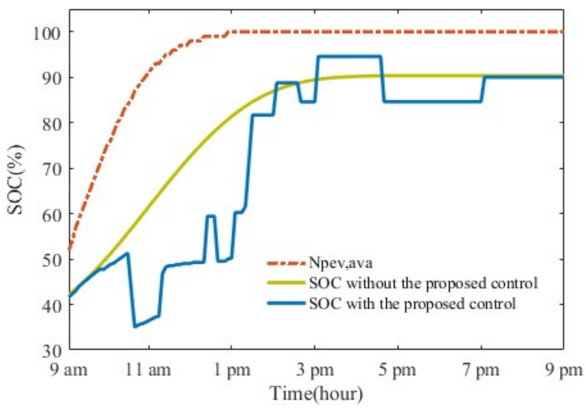

Fig. 5. SOC of the PEVs with and without the proposed control, and N_{PEV},ava*Cbattery.

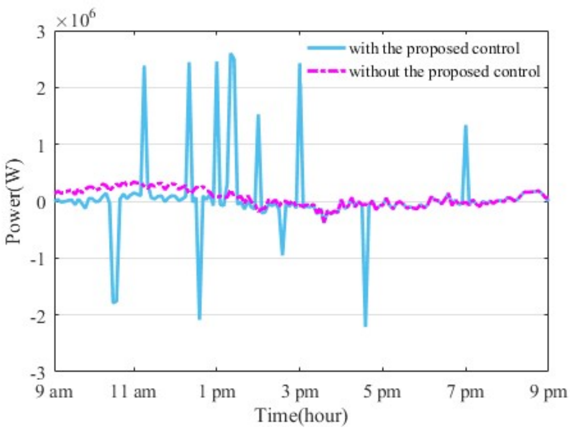

Fig.6. Power injected to the commercial building from main grid.

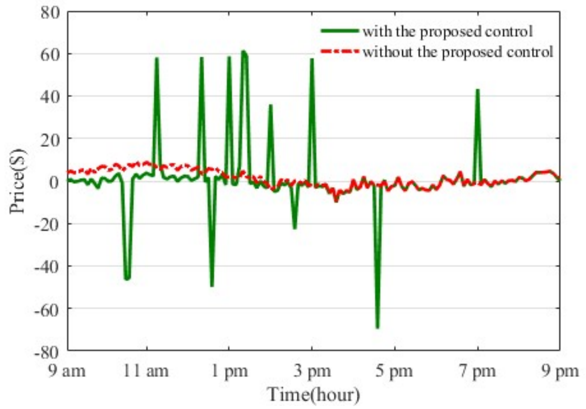

Fig.7. Cost of power injected to the commercial building from main grid.

TABLE 3. TOTAL COST OF INJECTED ELECTRICITY TO THE COMMERCIAL MICROGRID FROM THE MAIN GRID

Method	Operational cost	Improvement
Without the proposed control	206.6003 ($)	-
The proposed control with B=0.99	139.5153 ($)	32.47%
The proposed control with B=0.95	137.3132 ($)	33.54%
The proposed control with B=0.90	128.7805 ($)	37.67%

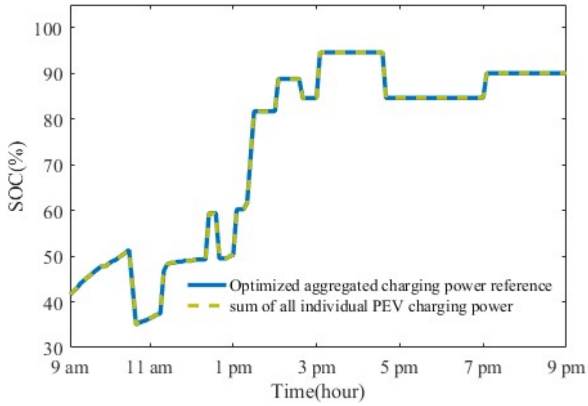

Fig. 8. The calculated aggregated charging reference for PEVs and the sum of all individual PEV charging power.

VI. CONCLUSION

Increasing the number of PEVs as a bulk load demand along with the renewable energy resources which have an unpredictable nature imposes some challenges for the future microgrids and the main grid. One of the most important challenges is the power imbalance between the generation and the consumption. In order to improve the demand response in a commercial microgrid with the purpose of minimizing its operational cost this paper presents a two stage predictive control approach for the energy management by considering the uncertainty in electricity prices which is incorporated by the CVaR in the optimization problem. It is assumed that the employees arrive at the commercial building in the morning stochastically and connect their PEVs to the charging station and disconnect it at 9 P.M. when they depart. Using the proposed approach and considering the risk associated with the electricity price, the PEVs are mainly charged during the off-peak-demand or when the electricity price is low. In this way, the total operational cost of the commercial building has noticeably decreased by 32.47%, 33.54% and 37.67% with β = 0.99, β = 0.95 and β = 0.90, respectively. In addition, by using the second stage of the proposed control approach, all the individual PEVs are charged in a way that the aggregated power reference is tracked appropriately. Any future work could contain a design of fully stochastic control for the PEVs control section, an analysis of different power sources and their associated costs, a more detailed model for the energy of the leaving PEVs, and a full cooperation between the residential buildings and the commercial buildings.

APPENDIX

$C_{Battery} = 20kWh$, $P_{PEV,\max} = 4kW$, $E_{km} = 0.2\, {kW}/{km}$, $c = 1/12$.

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